Uplift Modeling with Delayed Feedback: Identifiability and Algorithms

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Abstract

Uplift modeling has obtained significant attention, with broad applications in medicine, economics, and marketing. For example, in a push notification scenario, accurately estimating the uplift of different push frequencies on user activation and notification switch close rate is critical for balancing user experience and business goals. Existing methods only use binary labels, i.e., convert or not within the observational window. However, they ignore time information (e.g., users who convert on day 1 vs. day 14 reflect different sensitivities) and fail to model potential closures outside the window, i.e., due to treatments always taking time to manifest causal impacts on outcomes, the potential outcomes of interest cannot be observed promptly and accurately. Failing to account for these issues can result in skewed uplift modeling. To address this gap, this work examines how observation timing influences the assessment of uplift by explicitly modeling the potential response time. Theoretical analysis establishes the conditions for identifiability under delayed feedback scenarios. We introduce CFR-DF (Counterfactual Regression with Delayed Feedback), a systematic framework that jointly learns both the latent response times and the underlying potential outcomes. Empirical evaluations on synthetic and real-world datasets, including an A/B test with over 1 billion users for 14 days, validate the approach, demonstrating its ability to handle temporal delays and improve estimation accuracy compared to previous uplift modeling methods.

Introduction

Uplift modeling using observational data is a fundamental problem that applies to a wide variety of areas (Alaa and Van Der Schaar 2017; Alaa, Weisz, and Van Der Schaar 2017; Hannart et al. 2016). For example, in a push notifications scenario, inappropriate push frequencies often trigger users to close notification switches, directly harming long-term user retention. Modeling the uplift of different push frequencies on user closure and activation behavior is therefore essential for personalized push strategies. Unlike using observed outcomes, Uplift modeling accounts for the difference between factual outcomes and counterfactual outcomes when making decisions. The challenge lies in accurately estimating uplift due to unobserved counterfactual outcomes with alternative treatment (Holland 1986).

Many methods have been proposed to estimate uplift from observational data. For instance, representation learning-based approaches learn a covariate representation that is independent of the treatment to overcome the covariate shift between the treatment and control groups (Johansson, Shalit, and Sontag 2016; Shalit, Johansson, and Sontag 2017; Shi, Blei, and Veitch 2019; Yao et al. 2018). The tree-based approach includes Bayesian inference and random forest methods for nonparametric estimation (Chipman, George, and McCulloch 2010; Wager and Athey 2018). The generative model-based approaches use the widely adopted variational autoencoder and generative adversarial network to generate individual counterfactual outcomes (Louizos et al. 2017; Yoon, Jordon, and Van Der Schaar 2018).

Existing methods ignore time information (e.g., users who convert on day 1 vs. day 14 reflect different sensitivities) and failure to model potential closures outside the window, i.e., due to treatments always taking time to manifest causal impacts on outcomes, the potential outcomes of interest cannot be observed promptly and accurately (Chapelle 2014; Yoshikawa and Imai 2018). Failing to account for these issues can pose a critical challenge in practice: as in Figure 1(a), if the observation window is too short, some samples will be incorrectly marked as negative whose conversion will occur in the future. Ignoring such delays in outcome response can lead to biased estimates of uplift. In addition, though Jaroszewicz and Rzepakowski (2014) proposes to consider delay in uplift modeling, they do not discuss the identifiability and learning algorithm for deep learning.

In this paper, we first formalize the uplift modeling problem in the presence of delayed feedback. In addition to only considering the uplift of treatment on outcome, we also consider different potential response times with different treatments, since treatment may affect response time, e.g., users who receive more pushed notifications close more quickly. Therefore, as in Figure 1(a), given the treatment w for an individual, even the eventual outcome of interest $Y(w)$ is positive, e.g., the user will eventually close the notification switch, we can only observe the positive conversion $\tilde{Y}(w) = 1$ when the potential response time is less than the observation time ($D(w) \leq T$), while observing the false negative outcome $\tilde{Y}(w) = 0$ vise versa. Instead, when

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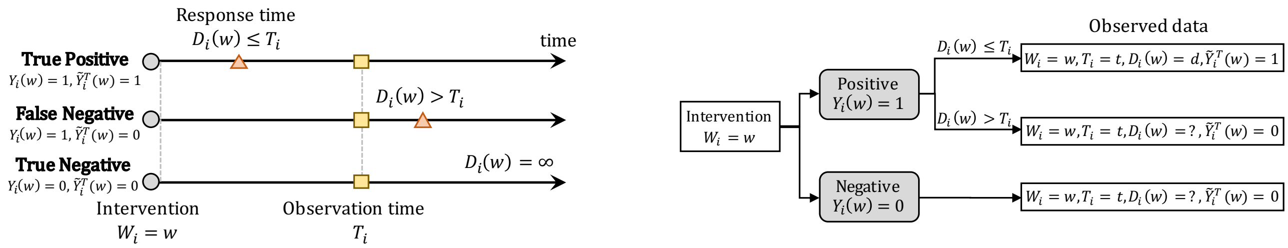


(a) Three types of delayed feedback scenarios.

(b) Observed data with various potential outcomes.

Figure 1: Illustrations for false negative (left) and data format (right) under delayed feedback.

the eventual outcome $Y(w)$ is negative, e.g., the user never closes the notification switch, then we observe the negative outcome ($\tilde{Y}(w) = 0$) regardless of the observation time. Figure 1(b) illustrates the format of the observed data with an additional challenge compared to the traditional scenario, that is, we could not obtain the exact value of the response time and the true label if the positive feedback did not occur before the observation time.

To address the above issues, we study the impact of observation time on uplift modeling. Theoretically, we prove that the eventual potential outcomes are identifiable in the whole population, which is essential for treatment allocation. For subgroups in which individuals always have positive eventual outcomes regardless of treatment, we also show the identifiability of potential response times. Furthermore, we propose a principled learning approach that extends counterfactual regression to delayed feedback outcomes, named CFR-DF, to simultaneously predict potential outcomes and potential response times. Finally, we validate the proposed method on both synthetic and real-world datasets. The main contributions are summarized below:

- We formalize the uplift modeling problem with delayed feedback, in which treatment takes time to produce an uplift on the outcome.
- We theoretically prove the eventual potential outcome is identifiable, and also show the identifiability of potential response times on the Sure Things stratum.
- We propose a principled learning algorithm, called CFR-DF, that utilizes the EM algorithm to estimate both eventual potential outcomes and potential response times.
- We perform extensive experiments on both synthetic and real-world datasets, including an A/B test with over 1 billion users, to show the effectiveness of our approach.

Related Work

In recent years, estimating treatment effects for uplift model has gained widespread attention. Early research focuses on discrete modeling, ranging from tree-based (Chipman, George, and McCulloch 2010; Wager and Athey 2018) and propensity methods (Rosenbaum and Rubin 1983; Li et al. 2023b,a, 2024b) to deep learning (Johansson, Shalit, and Sontag 2016; Shalit, Johansson, and Sontag 2017; Yao et al. 2018; Shi, Blei, and Veitch 2019; Zhou et al. 2025b; Zheng et al. 2025) and generative counterfactual synthesis (Louizos et al. 2017; Yoon, Jordon, and Van Der Schaar 2018; Wang et al. 2024; Zhou et al. 2025a; Wu et al. 2025). Continuous treatment estimation has also advanced through discretization and curve continuity modeling (Schwab et al. 2020; Bica, Jordon, and van der Schaar 2020; Nie et al. 2021; Li et al. 2024a; Zhang et al. 2025a). Based on this, recent methods integrate semi-supervised learning (Kügelgen et al. 2020; Huang et al. 2022; Miao et al. 2023; Yang et al. 2022), active learning (Jesson et al. 2021; Piskorz et al. 2025; Zhang et al. 2025b), and multi-task frameworks (Mondal, Majumder, and Chaoji 2022; Liu et al. 2023, 2022; Huang et al. 2024; Sun and Chen 2024; Liu et al. 2025) to address complex scenarios. Uplift modeling applies these methods for intervention optimization (Zhao and Harinen 2019; Ai et al. 2022; Fernández-Loría and Provost 2022; Li et al. 2023c; Sun et al. 2023; Chen et al. 2024; Huang et al. 2024). However, existing methods typically assume immediate observation. To bridge this gap, we simultaneously model the outcomes and response times to distinguish true negatives from delayed positives.

Uplift Modeling with Delayed Feedback

Notation and Setup

In this paper, we first focus on the binary treatment (the results can be easily generalized to multi-value treatment, which will be discussed later). Suppose we have n units, for each unit i, the covariate and the assigned treatment are denoted as $X_i \in \mathcal{X} \subset \mathbb{R}^m$ and $W_i \in \mathcal{W} = \{0, 1\}$, where $W_i = 1$ means receiving the treatment and $W_i = 0$ means not receiving the treatment, respectively. Compared to the previous uplift modeling methods, we consider the response time from the imposing treatment to producing an influence on the outcome. Specifically, under the potential outcome framework (Rubin 1974; Neyman 1990), let $Y_i(w) \in \mathcal{Y} = \{0, 1\}$ be the binary outcome at the eventual time with treatment w, e.g., whether a user will eventually close, as the primary outcome of interest, and we call unit with $Y_i(w) = 1$ as a positive sample. Without loss of generality, the time at which the treatment W_i is imposed on unit i is taken as the start time. Let $D_i(w)$ be the response time for individuals with $Y_i(w) = 1$ to produce positive feedback, and we set $D_i(w) = \infty$ for individuals with $Y_i(w) = 0$. Given an observation time T_i, we see a positive feedback at T_i, denoted as $\tilde{Y}_i^T(w) = 1$, if and only if individual i is a positive sample $Y_i(w) = 1$ with the response time $D_i(w) \leq T_i$, and marked as *true positive*. However, we would see false negative feedback $\tilde{Y}_i^T(w) = 0$ at the observation time T_i, when the response time is greater than the observation time, i.e., $D_i(w) > T_i$ with $Y_i(w) = 1$, and marked as *false negative*. For samples that never yield positive outcomes, we observe negative feedback $\tilde{Y}_i^T(w) = 0$ for all observation times T_i, and marked as *true negative*. Since each unit can be only assigned with one treatment, we always observe the corresponding outcome to be either $\tilde{Y}_i^T(0), D_i(0)$ or $\tilde{Y}_i^T(1), D_i(1)$, but not both, which is the fundamental problem of causal inference (Holland 1986; Morgan and Winship 2015).

Parameters of Interest

We consider two meaningful parameters of interest. For simplification, we drop the subscript i hereafter. First, **unlike previous studies that focused on the uplift of treatment on current observed outcomes,** i.e., $\tau^T(x) = \mathbb{E}[\tilde{Y}^T(1) - \tilde{Y}^T(0) \mid X = x]$, **we focused on the uplift on the eventual outcomes,** i.e., $\tau(x) = \mathbb{E}[Y(1) - Y(0) \mid X = x]$. The latter poses two challenges: first, the confounding bias introduced by covariates, which is similar to previous studies; second, how to recover the eventual outcome Y of interest from the observed outcome $\tilde{Y}^T$ at time T.

Next, we show that individuals can be divided into four strata by considering the joint potential outcomes $(Y(0), Y(1))$, as shown in Table 1. From a policy learning perspective, it is clear that treatment should be given to *Persuadables* and not given to *Do-Not-Disturbers* strata, respectively. For individuals in the *Lost Causes* stratum, either of the treatments is reasonable because the results show no difference. When considering individuals in the *Sure Things* stratum, despite having both $Y(0) = 1$ and $Y(1) = 1$ for the eventual outcomes, it is meaningful to study the uplift modeling of the treatment on the response times. Formally, the causal estimand of interest is $\mathbb{E}[D(1) - D(0) \mid Y(0) = 1, Y(1) = 1, X = x]$. For the other three strata, since there exists a treatment w such that $Y(w) = 0$, the corresponding response time can be regarded as $D(w) = \infty$, resulting in uplift of treatment on response time being ill-defined.

We summarize the causal estimand of interest as follows.

- Uplift on the eventual outcome: $\tau(x) = \mathbb{E}[Y(1) - Y(0) \mid X = x]$;
- Uplift on the response time: $\tau_D(x) = \mathbb{E}[D(1) - D(0) \mid Y(0) = 1, Y(1) = 1, X = x]$.

Identifiability Results

We then discuss the identifiability of the causal parameters of interest. Besides some widely used assumptions, such as positivity, consistency, and SUTVA, we adopt the following common assumptions in uplift modeling.

Assumption 1 (Unconfoundedness)

$$W \perp\!\!\!\perp (D(0), D(1), \tilde{Y}^t(0), \tilde{Y}^t(1)) \mid X \quad \textit{for all} \quad t > 0.$$

Assumption 2 (Time Independence)

$$T \perp\!\!\!\perp (D(0), D(1), \tilde{Y}^t(0), \tilde{Y}^t(1), W) \mid X \quad \textit{for all} \quad t > 0.$$

Assumption 3 (Time Sufficiency) $\inf\{d : F_D^{(w)}(d \mid Y(w) = 1, X) = 1\} < \inf\{t : F_T(t) = 1\}$ *for* $w = 0, 1$, *where* $F(\cdot)$ *is the cumulative distribution function (cdf).*

Assumption 4 (Monotonicity) $Y(0) \leq Y(1)$.

Assumption 5 (Principal Ignorability) $(W, Y(w)) \perp\!\!\!\perp D(1-w) \mid Y(1-w), X$ *for* $w = 0, 1$.

Among them, unconfoundedness is also known as the no unmeasured confounders assumption, which means all variables that affect both treatment and potential outcomes are included in X. Time independence holds since the observation occurs after the treatment, and the observation does not affect the potential response times $D(w)$ and the potential outcomes $\tilde{Y}^t(w)$ at a given time $t > 0$ for $w = 0, 1$. Time Sufficiency means that we need a subset of individuals (not all) with observed outcomes $\tilde{Y} = 1$ to identify eventual potential outcomes, which is a necessary condition for studying survival analysis. The monotonicity assumption is plausible in many applications when the effect of the decision on the outcome is non-negative for all individuals, e.g., the more push notifications are sent, the quicker the user closes the notification switch. Principal Ignorability requires that the expectations of the potential outcomes do not vary across principal strata conditional on the covariates. It is widely used in applied statistics (Imai and Jiang 2023; Ben-Michael, Imai, and Jiang 2024).

We next provide the identifiability results of three causal parameters[1].

Theorem 1 *Under Assumptions 1-3, the uplift on the eventual outcome* $\tau(x)$ *is identifiable.*

In addition, with monotonicity assumption and principal ignorability assumption, we can identify the uplift on potential response times in the *Sure Things* stratum $\tau_D(x)$.

Theorem 2 *Under Assumptions 1-5, we can identify the uplift on the response time in the Sure Things stratum* $\tau_D(x) = \mathbb{E}[D(1) - D(0) \mid Y(0) = 1, Y(1) = 1, X = x]$.

Note that though assigning treatment on *Sure Things* stratum has no effect on $\tau(x)$, if $\tau_D(x)$ is large, it may still be a desirable treatment assignment. For example, even if a customer will buy this commodity, an advertisement may make customers purchase more quickly, enabling merchants to recover costs.

CFR-DF: Counterfactual Regression with Delayed Feedback

In this section, we propose a principled learning approach to perform **C**ounter**F**actual **R**egression with **D**elayed **F**eedback on outcomes, named CFR-DF. Specifically, CFR-DF consists of two sets of models to predict the eventual potential outcomes, i.e., $\mathbb{P}(Y(0) = 1 \mid X = x)$ and $\mathbb{P}(Y(1) = 1 \mid X = x)$ and the potential response times, i.e., $\mathbb{P}(D(0) = d \mid$

[1]All proofs can be found in the Appendix in arXiv version.

Group	$Y(0)$	$Y(1)$	$D(0)$	$D(1)$	Preferred treatment
Sure Things	1	1	✓	✓	Depends on $\tau_D(x)$
Persuadables	0	1	∞	✓	Treatment ($W=1$)
Do-Not-Disturbers	1	0	✓	∞	Control ($W=0$)
Lost Causes	0	0	∞	∞	Either ($W=0$ or 1)

Table 1: The units are divided into four strata based on the joint potential outcomes $(Y(0), Y(1))$.

$X=x, Y(0)=1)$ and $\mathbb{P}(D(1)=d \mid X=x, Y(1)=1)$, respectively, the former of which can be flexibly exploited from previous uplift modeling methods in the following framework, and we take the widely used counterfactual regression (CFR) (Shalit, Johansson, and Sontag 2017) for illustration purpose.

Recall that in Figure 1(b), we show two possible observed data formats. On the one hand, the probability of observing positive feedback $\tilde{Y}^T=1$ with response time $D=d$ at time $T=t>d$:

$$\begin{aligned}
&p(\tilde{Y}^T=1, D=d \mid X=x, W=w, T=t)\\
&=p(Y=1, D=d \mid X=x, W=w)\\
&=\mathbb{P}(Y(w)=1 \mid X=x, W=w)\\
&\quad\cdot p(D(w)=d \mid X=x, W=w, Y(w)=1)\\
&=\mathbb{P}(Y(w)=1 \mid X=x) p(D(w)=d \mid X=x, Y(w)=1),
\end{aligned}$$

where the first equality follows from time independence, the second equality follows from the consistency assumption, and the last equality follows from the unconfoundedness assumption. To avoid misleading, we use $p(\cdot)$ to represent density, and $\mathbb{P}(\cdot)$ to represent probability.

On the other hand, by the law of total probabilities, and again using the conditional independence of observation time, the probability of not having observed positive feedback at time $T=t>d$ is:

$$\begin{aligned}
&\mathbb{P}(\tilde{Y}^T=0 \mid X=x, W=w, T=t)\\
=&\mathbb{P}(Y=0 \mid X=x, W=w) \mathbb{P}(\tilde{Y}^t=0 \mid X=x, W=w, Y=0)\\
+&\mathbb{P}(Y=1 \mid X=x, W=w) \mathbb{P}(\tilde{Y}^t=0 \mid X=x, W=w, Y=1),
\end{aligned}$$

where $\mathbb{P}(Y=0 \mid X=x, W=w)$ is equivalent to $\mathbb{P}(Y(w)=0 \mid X=x)$ by unconfoundedness assumption, with similar result holds for $\mathbb{P}(Y=1 \mid X=x, W=w)$. In addition, we have $\mathbb{P}(\tilde{Y}^t=0 \mid X=x, W=w, Y=0)=1$, due to eventual outcome $Y=0$ implies $\tilde{Y}^t=0$ for all $t>0$. By noting the equivalence between $(\tilde{Y}^t(w)=0, Y(w)=1)$ and $(D(w)>t, Y(w)=1)$:

$$\begin{aligned}
&\mathbb{P}(\tilde{Y}^t=0 \mid X=x, W=w, Y=1)\\
=\ &\mathbb{P}(D(w)>t \mid X=x, Y(w)=1)\\
=&\int_t^{\infty} p(D(w)=u \mid X=x, Y(w)=1) du.
\end{aligned}$$

With the above results, we have the probability of $\tilde{Y}^T=0$ at time $T=t$ is:

$$\begin{aligned}
&\mathbb{P}(\tilde{Y}^T=0 \mid X=x, W=w, T=t)\\
&=\mathbb{P}(Y(w)=0 \mid X=x)\\
&+\mathbb{P}(Y(w)=1 \mid X=x)\\
&\cdot \int_t^{\infty} p(D(w)=u \mid X=x, Y(w)=1) du,
\end{aligned}$$

which can be represented by two sets of models in CFR-DF.

Then we introduce the representation learning model structure to learn $\mathbb{P}(Y(w)=1 \mid X=x)$ and $p(D(w)=d \mid X=x, Y(w)=1)$. Let $h^Y(\Phi^Y(x), w)$ be the prediction model for the eventual potential outcomes $\mathbb{P}(Y(w)=1 \mid X=x)$, and $h^D(\Phi^D(x), w, d)$ be the prediction model for the potential response times $p(D(w)=d \mid X=x, Y(w)=1)$, where $\Phi^Y: \mathcal{X} \rightarrow \mathcal{R}^Y$ and $\Phi^D: \mathcal{X} \rightarrow \mathcal{R}^D$ are the covariate representations, $\mathcal{R}^Y$ and $\mathcal{R}^D$ are the representation spaces, and $h^Y: \mathcal{R}^Y \times\{0,1\} \rightarrow \mathcal{Y}$ and $h^D: \mathcal{R}^D \times\{0,1\} \times \mathbb{R}^{+} \rightarrow \mathbb{R}^{+}$ are the prediction heads, respectively. We take the Integral Probability Metric (IPM) distance induced by the representations as a penalty term, to control the generalization error caused by covariate shift between the treatment and control groups.

We train the eventual potential outcome model by minimizing the derived negative log-likelihood with the IPM distance. Denote $p_i:=\mathbb{P}(Y_i(w_i)=1 \mid X=x_i, W=w_i, \tilde{Y}^T=y_i^t)$, we have

$$\begin{aligned}
&\ell(h^Y, \Phi^Y \mid p_1, \ldots, p_n)=-\sum_i p_i \log h^Y(\Phi^Y(x_i), w_i)\\
&-\sum_i(1-p_i) \log (1-h^Y(\Phi^Y(x_i), w_i))\\
&+\alpha^Y \cdot \operatorname{IPM}_{\mathcal{G}^Y}(\{\Phi^Y(x_i)\}_{i: w_i=0},\{\Phi^Y(x_i)\}_{i: w_i=1}),
\end{aligned}$$

where $\mathcal{G}^Y$ is a family of functions $g^Y: \mathcal{R}^Y \rightarrow \mathcal{Y}$, and α^Y is a hyper-parameter. For two probability density functions p, q defined over $\mathcal{S} \subseteq \mathbb{R}^d$, and for a function family G of functions $g: \mathcal{S} \rightarrow \mathbb{R}$, the IPM distance is $\operatorname{IPM}_{\mathrm{G}}(p, q):=\sup_{g \in \mathrm{G}}\left|\int_{\mathcal{S}} g(s)(p(s)-q(s)) ds\right|$. Similarly, we train the potential response time model by:

$$\begin{aligned}
&\ell(h^D, \Phi^D \mid p_1, \ldots, p_n)=\sum_{i: \tilde{y}_i^t=1} \log h^D(\Phi^D(x_i), w_i, d_i)\\
&+\sum_{i: \tilde{y}_i^t=0} p_i \log \int_{t_i}^{\infty} h^D(\Phi^D(x_i), w_i, u) du\\
&+\alpha^D \cdot \operatorname{IPM}_{\mathcal{G}^D}(\{\Phi^D(x_i)\}_{i: w_i=0},\{\Phi^D(x_i)\}_{i: w_i=1}),
\end{aligned}$$

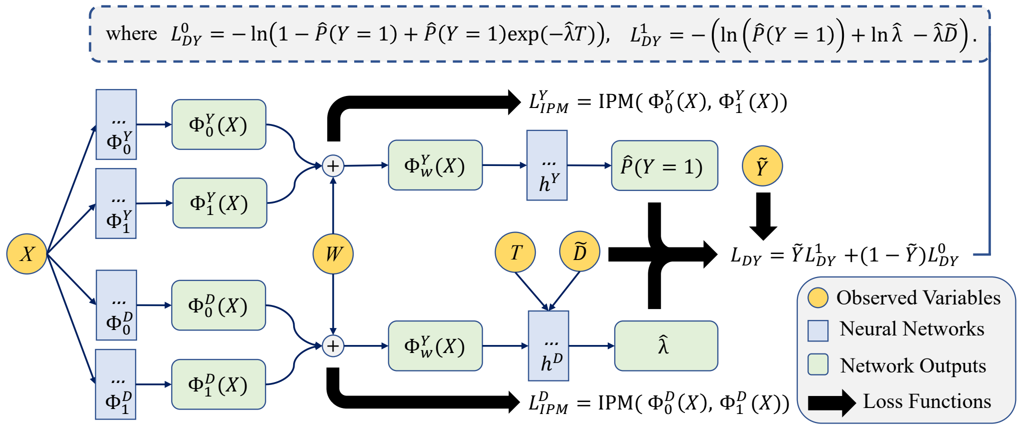


Figure 2: Overview of CFR-DF Architecture. For the representation block, we use multi-layer neural networks Φ with ELU activation function to learn representation and each network has two/three layers with m_X units, respectively. Then, we use a single-layer network h^Y with Sigmoid activation to achieve $\hat{P}(Y=1)$ and a single-layer network h^D with SoftPlus sigmoid activation to achieve $\hat{\lambda}$.

with $\mathcal{G}^D$ and α^D defined similarly. We summarize the algorithm, including the detailed backbone and hyper-parameters choices, in the Appendix in our arXiv version.

Implementation of CFR-DF. We now show the empirical computation details for computing the integration, i.e., $\mathbb{P}(D(w) > t \mid X = x, Y(w) = 1)$. We first introduce the parametric model method. For example, one can assume that the potential delayed feedback times obey exponential models for both treatment and control groups. Specifically, let $\mathbb{P}(D(w) = u \mid X = \mathbf{x}, Y(w) = 1) = \lambda_w(\mathbf{x})\exp(-\lambda_w(\mathbf{x})u)$ for $w = 0, 1$, we have $\int_t^\infty \mathbb{P}(D(w) = u \mid X = \mathbf{x}, Y(w) = 1)du = \int_t^\infty \lambda_w(\mathbf{x})\exp(-\lambda_w(\mathbf{x})u)\,du = \exp(-\lambda_w(\mathbf{x})t)$. In addition, the estimation of potential delayed feedback times can be further extended to a nonparametric model, which can be found in our arXiv version.

Scalability to Non-Binary Treatments. Our work can be naturally extended to non-binary treatments with the identifiability results of true uplift modeling in all strata, i.e., $\mathbb{E}[Y(w) \mid X = x]$ for all $w \in \mathcal{W}$. By defining delayed feedback time $D(w)$ for all $w \in \mathcal{W}$ similarly and following a similar argument of our identifiability proof, and substitute $Y(0)$ and $Y(1)$ to $Y(w)$ for all $w \in \mathcal{W}$, the true uplift modeling $\mathbb{E}[Y(w) \mid X = x]$ for all $w \in \mathcal{W}$ can be identified similarly. Moreover, in the proposed time-to-event-based uplift modeling problem setup with delayed feedback, the outcome of interest has to be binary to ensure well-definedness. To verify the scalability to non-binary treatments, we conduct an online A/B test over 1 billion users with 13 possible treatments. See the experiment part for a detailed discussion.

Experiments

Baselines and Evaluation Protocols

We evaluate our framework CFR-DF, and its variant without balancing regularization (TAR-DF), in the task of (i) estimating uplift modeling on the eventual outcome and (ii) estimating uplift modeling on the response time in the Sure Things stratum. We compare our method with the following methods: **T-learner** (Künzel et al. 2019), representation-based algorithms including **CFR** (Shalit, Johansson, and Sontag 2017), **SITE** (Yao et al. 2018), **Dragonnet** (Shi, Blei, and Veitch 2019), **CFR-ISW** (Hassanpour and Greiner 2019), **DR-CFR** (Hassanpour and Greiner 2020) and **DER-CFR** (Wu et al. 2022), and generative algorithms **CEVAE** (Louizos et al. 2017) and **GANITE** (Yoon, Jordon, and Van Der Schaar 2018). Following the previous studies (Shalit, Johansson, and Sontag 2017; Yao et al. 2018; Wu et al. 2022), we evaluate the performance of uplift modeling using the following two metrics:

$$\epsilon_{\text{PEHE}} = \frac{1}{N}\sum_{i=1}^{N}\left((\hat{y}_i(1) - \hat{y}_i(0)) - (y_i(1) - y_i(0))\right)^2,$$

$$\epsilon_{\text{ATE}} = \left|\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i(1) - \hat{y}_i(0) - (y_i(1) - y_i(0)))\right|,$$

where $\hat{y}_i$ and y_i are predicted and true outcomes. The code is at https://github.com/ChunyuanZheng/delay.

Datasets

Synthetic Datasets. Since the true potential outcomes are rarely available for real-world, we conduct simulation studies using synthetic datasets as follows. The observed covariates are generated from $X \sim \mathcal{N}(0, I_{m_X})$, where I_{m_X} denotes m_X-degree identity matrix. The observed treatment $W \sim \text{Bern}(\pi(X))$, where $\pi(X) = \mathbb{P}(W = 1 \mid X) = \sigma(\theta_W \cdot X)$, $\theta_W \sim U(-1, 1)$, and $\sigma(\cdot)$ denotes the sigmoid function. For the eventual potential outcomes, we generate the control outcome $Y(0) \sim \text{Bern}(\sigma(\theta_{Y0} \cdot X^2 + 1))$, and the treated outcome $Y(1) \sim \text{Bern}(\sigma(\theta_{Y1} \cdot X^2 + 2))$, where $\theta_{Y0}, \theta_{Y1} \sim U(-1, 1)$. In addition, we generate the potential response time $D(0) \sim \text{Exp}(\exp(\theta_{D0} \cdot X)^{-1})$, and $D(1) \sim \text{Exp}(\exp(\theta_{D1} \cdot X - b_D)^{-1})$, where $\theta_{D0}, \theta_{D1} \sim U(-0.1, 0.1)$, and b_D *controls the heterogeneity of response time functions*. The observation time is generated via $T \sim$

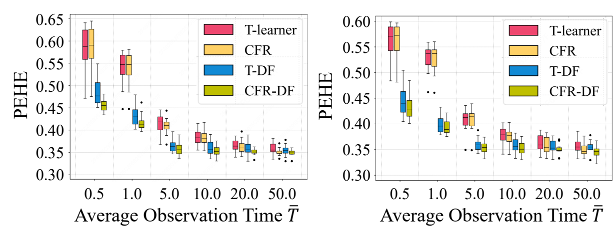
Method	Toy ($b_D = 0$)		Toy ($b_D = 0.5$)		Toy ($b_D = 1$)	
	ϵ_{PEHE}	ϵ_{ATE}	ϵ_{PEHE}	ϵ_{ATE}	ϵ_{PEHE}	ϵ_{ATE}
T-learner	0.535 ± 0.041	0.069 ± 0.024	0.514 ± 0.036	0.028 ± 0.017	0.523 ± 0.028	0.109 ± 0.017
CFR	0.536 ± 0.042	0.071 ± 0.025	0.517 ± 0.037	0.025 ± 0.016	0.523 ± 0.028	0.108 ± 0.016
SITE	0.630 ± 0.058	0.023 ± 0.041	0.646 ± 0.077	0.026 ± 0.020	0.654 ± 0.039	0.128 ± 0.045
Dragonnet	0.612 ± 0.080	0.101 ± 0.055	0.499 ± 0.023	0.028 ± 0.024	0.504 ± 0.018	0.095 ± 0.032
CFR-ISW	0.552 ± 0.057	0.064 ± 0.040	0.602 ± 0.084	0.034 ± 0.024	0.590 ± 0.081	0.122 ± 0.023
DR-CFR	0.539 ± 0.030	0.071 ± 0.032	0.521 ± 0.044	0.032 ± 0.026	0.524 ± 0.038	0.107 ± 0.035
DER-CFR	0.548 ± 0.051	0.051 ± 0.029	0.540 ± 0.037	0.066 ± 0.043	0.568 ± 0.034	0.162 ± 0.032
CEVAE	0.661 ± 0.077	0.123 ± 0.039	0.661 ± 0.077	0.122 ± 0.039	0.661 ± 0.077	0.122 ± 0.039
GANITE	0.672 ± 0.074	0.173 ± 0.037	0.662 ± 0.075	0.147 ± 0.036	0.655 ± 0.076	0.122 ± 0.035
TAR-DF	0.416 ± 0.019	0.021 ± 0.008	0.432 ± 0.013	0.017 ± 0.014	0.407 ± 0.016	0.013 ± 0.007
CFR-DF	**0.409 ± 0.018**	**0.019 ± 0.008**	**0.404 ± 0.014**	**0.013 ± 0.009**	**0.395 ± 0.013**	**0.011 ± 0.009**

Table 2: Performance comparison (MSE ± std) on synthetic datasets with varying b_D.

$\text{Exp}(\lambda)$, where λ is the rate parameter of the exponential distribution, and we set $\lambda = 1$ in our experiments, i.e., the average observation time is $\bar{T} = \lambda^{-1} = 1$. Finally, the observed outcome is $\tilde{Y}^T(W) = W \cdot Y(1) \cdot \mathbb{I}(T \geq D(1)) + (1 - W) \cdot Y(0) \cdot \mathbb{I}(T \geq D(0))$, where $\mathbb{I}(\cdot)$ is the indicator function. Based on the data generation process described above, we sample $N = 20{,}000$ samples for training and $3{,}000$ samples for testing. We repeat each experiment 10 times to report the mean and standard deviation of the results (ϵ_{PEHE} and ϵ_{ATE}). Moreover, we vary the heterogeneity of response times by setting $b_D \in \{0, 0.5, 1\}$, named the dataset as **Toy** ($b_D = 0$), **Toy** ($b_D = 0.5$), and **Toy** ($b_D = 1$).

Real-World Datasets. We also evaluate our CFR-DF on three widely-adopted real-world datasets: **AIDS** (Hammer et al. 1997; Norcliffe et al. 2023), **Jobs** (LaLonde 1986; Shalit, Johansson, and Sontag 2017), and **Twins** (Almond, Chay, and Lee 2005; Wu et al. 2022). The **AIDS** dataset contains 1,156 patients in 33 AIDS clinical trial units and 7 National Hemophilia Foundation sites in the United States and Puerto Rico. The **Jobs** dataset is built upon randomized controlled trials and aims to assess the effects of job training programs on employment status. The **Twins** dataset is derived from all twins born in the USA between the years 1989 and 1991, and is utilized to assess the influence of birth weight on mortality within one year. For all three datasets, we use the observed covariate X, and following the same procedure for generating synthetic datasets, we generate treatment W, potential outcomes $Y(0)$ and $Y(1)$, potential response times $D(0)$ and $D(1)$, observation time T and factual outcomes $\tilde{Y}^T(W)$. Then we randomly split the samples into training/test with an 8/2 ratio, with 10 repetitions.

Furthermore, we conduct an online A/B test on a real-world recommendation platform with 1 billion users for 14 days with 13 possible treatments from 0 to 12, representing the push notification number. In addition, due to we collect RCT data, therefore we use an X-net structure based on the DESCN (Zhong et al. 2022). using the proposed method as the experimental group and the baseline DESCN without considering delayed feedback as the control group to validate the effectiveness of the proposed method.



(a) **Toy** ($b_D = 0$). (b) **Toy** ($b_D = 1$).

Figure 3: Effects of varying average observation time on synthetic datasets with varying b_D.

Performance Comparison. We compare our method with the baselines for estimating the uplift in Table 2. The optimal and second-optimal performance are **bold** and underlined. First, the proposed CFR-DF stably outperforms the baselines, as the previous methods do not take into account the delayed feedback, leading to biased estimates of uplift modeling. Second, the TAR-DF method without using balancing regularization slightly degrades the performance compared to CFR-DF, due to the inability to resolve the confounding bias from covariate shift. These results highlight the scalability of our method to varying levels of observation times, showing its potential for real-world applications.

Ablation Studies. Figure 3 compares the proposed CFR-DF and its ablated versions for estimating uplift on the eventual outcome with varying average observation time, where TAR-DF does not perform balancing regularization, CFR does not consider delayed feedback, and neither is considered for T-learner. We have the following findings. The proposed CFR-DF and TAR-DF have significantly better performance when the observation time is shorter, due to their effective adjustment for delayed feedback. When increasing the average observation time leads to more delayed feedback being observed, we find improved performance for all four methods. When the observation time reaches 50, meaning almost all delayed feedbacks have been observed, our

Method	AIDS		Jobs		Twins	
	ϵ_{PEHE}	ϵ_{ATE}	ϵ_{PEHE}	ϵ_{ATE}	ϵ_{PEHE}	ϵ_{ATE}
T-learner	0.525 ± 0.052	0.091 ± 0.064	0.528 ± 0.043	0.085 ± 0.041	0.390 ± 0.071	0.050 ± 0.029
CFR	0.531 ± 0.046	0.083 ± 0.058	0.510 ± 0.035	0.064 ± 0.039	0.378 ± 0.057	0.029 ± 0.018
SITE	0.601 ± 0.031	0.082 ± 0.056	0.568 ± 0.045	0.064 ± 0.053	0.495 ± 0.087	0.139 ± 0.053
Dragonnet	0.546 ± 0.051	0.105 ± 0.042	0.555 ± 0.060	0.084 ± 0.060	0.440 ± 0.103	0.096 ± 0.067
CFR-ISW	0.592 ± 0.053	0.098 ± 0.032	0.499 ± 0.035	0.058 ± 0.056	0.392 ± 0.048	0.039 ± 0.023
DR-CFR	0.577 ± 0.056	0.078 ± 0.044	0.525 ± 0.077	0.079 ± 0.060	0.390 ± 0.046	0.039 ± 0.027
DER-CFR	0.609 ± 0.076	0.081 ± 0.074	0.503 ± 0.037	0.072 ± 0.043	0.398 ± 0.068	0.080 ± 0.066
CEVAE	0.623 ± 0.042	0.143 ± 0.019	0.638 ± 0.062	0.102 ± 0.058	0.526 ± 0.055	0.139 ± 0.027
GANITE	0.605 ± 0.034	0.136 ± 0.020	0.629 ± 0.053	0.151 ± 0.067	0.509 ± 0.056	0.139 ± 0.040
TAR-DF	0.521 ± 0.042	0.077 ± 0.030	0.453 ± 0.066	0.058 ± 0.030	0.366 ± 0.027	0.030 ± 0.018
CFR-DF	**0.499 ± 0.055**	**0.073 ± 0.031**	**0.438 ± 0.059**	**0.051 ± 0.031**	**0.357 ± 0.017**	**0.027 ± 0.015**

Table 3: Performance comparison (MSE ± SD) on **AIDS**, **Jobs**, and **Twins** datasets.

Method	Non-Mono		Non-Unconf	
	ϵ_{PEHE}	ϵ_{ATE}	ϵ_{PEHE}	ϵ_{ATE}
DragonNet	0.511	0.153	0.552	0.149
Surv Meta-Learner	0.540	0.017	0.516	0.103
Surv Uplift	0.536	0.015	0.498	0.073
Surv Causal Forest	0.495	0.023	0.465	0.036
CFR-DF	**0.461***	**0.002***	**0.437***	**0.028***

Table 4: Performance comparison (ϵ_{PEHE} and ϵ_{ATE}) under Non Monotonicity and Non unconfoundedness settings.

Metrics	Day3	Day7	Day14
TAU% ↑	**+0.017 ± 0.011**	**+0.019 ± 0.011**	**+0.017 ± 0.012**
CAU% ↑	**+0.015 ± 0.007**	**+0.016 ± 0.007**	**+0.018 ± 0.007**
TCU% ↓	**-0.002 ± 0.720**	**-0.333 ± 0.756**	**-0.600 ± 0.741**
CCU% ↓	**-0.152 ± 0.400**	**-0.255 ± 0.314**	**-0.259 ± 0.239**

Table 5: Results of the **Online A/B Test.** Metrics with an upward arrow indicate that higher values are preferable. Compared to the baseline, we report the results as **average difference ± confidence interval width** with p-value 0.05.

method performs similarly to the CFR. Further experiments on the performance of our methods in estimating uplift on the response times can be found in arXiv version.

Real-World Experiments. We conduct real-world experiments using **AIDS**, **Jobs**, and **Twins** datasets. Notably, treating AIDS requires long-term observation, job training takes time to cause changes in incomes, and infants also take time to observe their mortality outcomes (and thus study the effect on mortality), therefore it is reasonable to study the delayed feedback in such real-world applications. Table 3 demonstrates that CFR-DF outperforms all baselines on these real-world datasets, showcasing its effectiveness.

Robustness on Assumption Violation. We further investigate the robustness of CFR-DF when the strict assumptions of **Monotonicity** and **Unconfoundedness** are relaxed. Specifically, to simulate these violations, we conducted additional experiments by setting $E[Y(1)] = E[Y(0)]$ in the data generation process and randomly masking 20% of the covariates during training. We compare our method against uplift modeling and causal survival analysis baselines: DragonNet (Shi, Blei, and Veitch 2019), Survival Meta-Learner (Xu et al. 2023), Survival Uplift (Jaroszewicz and Rzepakowski 2014), and Survival Causal Forest (Cui et al. 2023). The results are reported in Table 4, where * indicates p-value < 0.05. It is observed that CFR-DF consistently yields the lowest ϵ_{PEHE} and ϵ_{ATE} errors compared to all baselines. This shows that our joint modeling strategy for outcomes and response times offers significant robustness against assumption violations.

Online A/B Test. Table 5 shows online A/B test results on a Douyin real-world platform, comparing our proposed method against the baseline without considering delayed feedback, using DESCN (Zhong et al. 2022) as the backbone. We evaluate performance with four metrics: Today active user (TAU), Today close user (TCU), Cumulated active user (CAU), and Cumulated close user (CCU). Overall, our method increases active users by 0.0176% and reduces close users by 0.259%, demonstrating its effectiveness in a non-binary treatment industry scenario. Moreover, these results also show that our method is backbone agnostic.

Conclusion

This paper studies the uplift modeling problem by further considering the response time needed for a treatment to produce a uplift on the outcome. Specifically, we propose a principled learning algorithm, called CFR-DF, to estimate both eventual potential outcomes and potential response times. Considering the widespread of delayed feedback outcomes, we believe such a study is meaningful for real-world applications, as it has already been proven effective in the Douyin dataset with over 1B users. A shortcoming of our study is the validity of the assumptions in practice, e.g., we need enough observation time to identify uplift modeling on the eventual potential outcome.

Acknowledgments

Z. Lin was supported by the NSF China (No. 62276004) and the State Key Laboratory of General Artificial Intelligence, and H. Li was supported by National Natural Science Foundation of China (623B2002).

References

Ai, M.; Li, B.; Gong, H.; Yu, Q.; Xue, S.; Zhang, Y.; Zhang, Y.; and Jiang, P. 2022. Lbcf: A large-scale budget-constrained causal forest algorithm. In *WWW*.

Alaa, A. M.; and Van Der Schaar, M. 2017. Bayesian inference of individualized treatment effects using multi-task gaussian processes. In *NeurIPS*.

Alaa, A. M.; Weisz, M.; and Van Der Schaar, M. 2017. Deep counterfactual networks with propensity-dropout. *arXiv preprint arXiv:1706.05966*.

Almond, D.; Chay, K. Y.; and Lee, D. S. 2005. The costs of low birth weight. *The Quarterly Journal of Economics*, 120(3): 1031–1083.

Ben-Michael, E.; Imai, K.; and Jiang, Z. 2024. Policy learning with asymmetric counterfactual utilities. *Journal of the American Statistical Association*, 119(548): 3045–3058.

Bica, I.; Jordon, J.; and van der Schaar, M. 2020. Estimating the effects of continuous-valued interventions using generative adversarial networks. In *NeurIPS*.

Chapelle, O. 2014. Modeling delayed feedback in display advertising. In *SIGKDD*.

Chen, J.; Wenjie, W.; Gao, C.; Wu, P.; Wei, J.; and Hua, Q. 2024. Treatment Effect Estimation for User Interest Exploration on Recommender Systems. In *SIGIR*.

Chipman, H. A.; George, E. I.; and McCulloch, R. E. 2010. BART: Bayesian additive regression trees. *The Annals of Applied Statistics*, 4(1): 266–298.

Cui, Y.; Kosorok, M. R.; Sverdrup, E.; Wager, S.; and Zhu, R. 2023. Estimating heterogeneous treatment effects with right-censored data via causal survival forests. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 85(2): 179–211.

Fernández-Loría, C.; and Provost, F. 2022. Causal classification: Treatment effect estimation vs. outcome prediction. *Journal of Machine Learning Research*, 23(59): 1–35.

Hammer, S. M.; Squires, K. E.; Hughes, M. D.; Grimes, J. M.; Demeter, L. M.; Currier, J. S.; Eron Jr, J. J.; Feinberg, J. E.; Balfour Jr, H. H.; Deyton, L. R.; et al. 1997. A controlled trial of two nucleoside analogues plus indinavir in persons with human immunodeficiency virus infection and CD4 cell counts of 200 per cubic millimeter or less. *New England Journal of Medicine*, 337(11): 725–733.

Hannart, A.; Pearl, J.; Otto, F.; Naveau, P.; and Ghil, M. 2016. Causal counterfactual theory for the attribution of weather and climate-related events. *Bulletin of the American Meteorological Society*, 97(1): 99–110.

Hassanpour, N.; and Greiner, R. 2019. CounterFactual Regression with Importance Sampling Weights. In *IJCAI*.

Hassanpour, N.; and Greiner, R. 2020. Learning Disentangled Representations for CounterFactual Regression. In *ICLR*.

Holland, P. W. 1986. Statistics and Causal Inference. *Journal of the American Statistical Association*, 81: 945–960.

Huang, Q.; Ma, J.; Li, J.; Sun, H.; and Chang, Y. 2022. Semi-iTE: semi-supervised individual treatment effect estimation via disagreement-based co-training. In *ECML/PKDD*.

Huang, Y.; Wang, S.; Gao, M.; Wei, X.; Li, C.; Luo, C.; Zhu, Y.; Xiao, X.; and Luo, Y. 2024. Entire chain uplift modeling with context-enhanced learning for intelligent marketing. In *WWW*.

Imai, K.; and Jiang, Z. 2023. Principal fairness for human and algorithmic decision-making. *Statistical Science*, 38(2): 317–328.

Jaroszewicz, S.; and Rzepakowski, P. 2014. Uplift modeling with survival data. In *SIGKDD Workshop on Health Informatics*.

Jesson, A.; Tigas, P.; van Amersfoort, J.; Kirsch, A.; Shalit, U.; and Gal, Y. 2021. Causal-bald: Deep bayesian active learning of outcomes to infer treatment-effects from observational data. In *NeurIPS*.

Johansson, F.; Shalit, U.; and Sontag, D. 2016. Learning representations for counterfactual inference. In *ICML*.

Kügelgen, J.; Mey, A.; Loog, M.; and Schölkopf, B. 2020. Semi-supervised learning, causality, and the conditional cluster assumption. In *UAI*.

Künzel, S. R.; Sekhon, J. S.; Bickel, P. J.; and Yu, B. 2019. Metalearners for estimating heterogeneous treatment effects using machine learning. *Proceedings of the national academy of sciences*, 116(10): 4156–4165.

LaLonde, R. J. 1986. Evaluating the econometric evaluations of training programs with experimental data. *The American economic review*, 604–620.

Li, H.; Lyu, Y.; Zheng, C.; and Wu, P. 2023a. TDR-CL: Targeted Doubly Robust Collaborative Learning for Debiased Recommendations. In *ICLR*.

Li, H.; Xiao, Y.; Zheng, C.; Wu, P.; and Cui, P. 2023b. Propensity Matters: Measuring and Enhancing Balancing for Recommendation. In *ICML*.

Li, H.; Zheng, C.; Ding, S.; Feng, F.; He, X.; Geng, Z.; and Wu, P. 2024a. Be Aware of the Neighborhood Effect: Modeling Selection Bias under Interference for Recommendation. In *ICLR*.

Li, H.; Zheng, C.; Wang, W.; Wang, H.; Feng, F.; and Zhou, X.-H. 2024b. Debiased recommendation with noisy feedback. In *SIGKDD*.

Li, H.; Zheng, C.; Wu, P.; Kuang, K.; Liu, Y.; and Cui, P. 2023c. Who should be Given Incentives? Counterfactual Optimal Treatment Regimes Learning for Recommendation. In *SIGKDD*.

Liu, D.; Tang, X.; Gao, H.; Lyu, F.; and He, X. 2023. Explicit feature interaction-aware uplift network for online marketing. In *SIGKDD*.

Liu, Q.; Luo, Y.; Wu, S.; Zhang, Z.; Yue, X.; Jin, H.; and Wang, L. 2022. RMT-Net: Reject-aware multi-task network for modeling missing-not-at-random data in financial credit scoring. *IEEE Transactions on Knowledge and Data Engineering*, 35(7): 7427–7439.

Liu, Y.; Shi, W.; Fu, C.; Jiang, Z.; Hua, Z.; and Carlson, D. 2025. MOTTO: A Mixture-of-Experts Framework for Multi-Treatment, Multi-Outcome Treatment Effect Estimation. In *SIGKDD*.

Louizos, C.; Shalit, U.; Mooij, J. M.; Sontag, D.; Zemel, R.; and Welling, M. 2017. Causal effect inference with deep latent-variable models. In *NeurIPS*.

Miao, J.; Chen, C.; Liu, F.; Wei, H.; and Heng, P.-A. 2023. Caussl: Causality-inspired semi-supervised learning for medical image segmentation. In *ICCV*.

Mondal, A.; Majumder, A.; and Chaoji, V. 2022. Memento: Neural model for estimating individual treatment effects for multiple treatments. In *CIKM*.

Morgan, S. L.; and Winship, C. 2015. *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. Cambridge University Press, second edition.

Neyman, J. S. 1990. On the application of probability theory to agricultural experiments. Essay on principles. Section 9. *Statistical Science*, 5: 465–472.

Nie, L.; Ye, M.; Nicolae, D.; et al. 2021. VCNet and Functional Targeted Regularization For Learning Causal Effects of Continuous Treatments. In *ICLR*.

Norcliffe, A.; Cebere, B.; Imrie, F.; Lio, P.; and van der Schaar, M. 2023. SurvivalGAN: Generating Time-to-Event Data for Survival Analysis. In *AISTATS*.

Piskorz, J.; Astorga, N.; Berrevoets, J.; and van der Schaar, M. 2025. Active Feature Acquisition for Personalised Treatment Assignment. In *AISTATS*.

Rosenbaum, P. R.; and Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1): 41–55.

Rubin, D. B. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational psychology*, 66: 688–701.

Schwab, P.; Linhardt, L.; Bauer, S.; Buhmann, J. M.; and Karlen, W. 2020. Learning counterfactual representations for estimating individual dose-response curves. In *AAAI*.

Shalit, U.; Johansson, F. D.; and Sontag, D. 2017. Estimating individual treatment effect: generalization bounds and algorithms. In *ICML*.

Shi, C.; Blei, D.; and Veitch, V. 2019. Adapting neural networks for the estimation of treatment effects. In *NeurIPS*.

Sun, Z.; and Chen, X. 2024. M 3 TN: Multi-Gate Mixture-of-Experts Based Multi-Valued Treatment Network for Uplift Modeling. In *ICASSP*.

Sun, Z.; He, B.; Ma, M.; Tang, J.; Wang, Y.; Ma, C.; and Liu, D. 2023. Robustness-enhanced uplift modeling with adversarial feature desensitization. In *ICDM*.

Wager, S.; and Athey, S. 2018. Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113(523): 1228–1242.

Wang, H.; Chen, Z.; Liu, Z.; Li, H.; Yang, D.; Liu, X.; and Li, H. 2024. Entire Space Counterfactual Learning for Reliable Content Recommendations. *IEEE Transactions on Information Forensics and Security*.

Wu, A.; Yuan, J.; Kuang, K.; Li, B.; Wu, R.; Zhu, Q.; Zhuang, Y.; and Wu, F. 2022. Learning decomposed representations for treatment effect estimation. *IEEE Transactions on Knowledge and Data Engineering*, 35(5): 4989–5001.

Wu, P.; Li, H.; Zheng, C.; Zeng, Y.; Chen, J.; Liu, Y.; Guo, R.; and Zhang, K. 2025. Learning Counterfactual Outcomes Under Rank Preservation. In *NeurIPS*.

Xu, Y.; Ignatiadis, N.; Sverdrup, E.; Fleming, S.; Wager, S.; and Shah, N. 2023. Treatment heterogeneity with survival outcomes. In *Handbook of matching and weighting adjustments for causal inference*, 445–482. Chapman and Hall/CRC.

Yang, X.; Hu, X.; Zhou, S.; Liu, X.; and Zhu, E. 2022. Interpolation-based contrastive learning for few-label semi-supervised learning. *IEEE Transactions on Neural Networks and Learning Systems*, 35(2): 2054–2065.

Yao, L.; Li, S.; Li, Y.; Huai, M.; Gao, J.; and Zhang, A. 2018. Representation learning for treatment effect estimation from observational data. In *NeurIPS*.

Yoon, J.; Jordon, J.; and Van Der Schaar, M. 2018. GANITE: Estimation of individualized treatment effects using generative adversarial nets. In *ICLR*.

Yoshikawa, Y.; and Imai, Y. 2018. A nonparametric delayed feedback model for conversion rate prediction. *arXiv preprint arXiv:1802.00255*.

Zhang, S.; Zhang, Y.; Chen, J.; and Sui, H. 2025a. Addressing correlated latent exogenous variables in debiased recommender systems. In *SIGKDD*.

Zhang, Z.; Wang, H.; Li, H.; and Lin, Z. 2025b. Active Treatment Effect Estimation via Limited Samples. In *ICML*.

Zhao, Z.; and Harinen, T. 2019. Uplift modeling for multiple treatments with cost optimization. In *DSAA*.

Zheng, C.; Yang, H.; Li, H.; and Yang, M. 2025. Unveiling Extraneous Sampling Bias with Data Missing-Not-At-Random. In *NeurIPS*.

Zhong, K.; Xiao, F.; Ren, Y.; Liang, Y.; Yao, W.; Yang, X.; and Cen, L. 2022. Descn: Deep entire space cross networks for individual treatment effect estimation. In *SIGKDD*.

Zhou, C.; Li, H.; Yao, L.; and Gong, M. 2025a. Counterfactual Implicit Feedback Modeling. In *NeurIPS*.

Zhou, C.; Li, Y.; Zheng, C.; Zhang, H.; Zhang, M.; Li, H.; and Gong, M. 2025b. A Two-Stage Pretraining-Finetuning Framework for Treatment Effect Estimation with Unmeasured Confounding. In *SIGKDD*.